

Longitudinal Driving Behavior in case of Emergency Situations: An Empirically Underpinned Theoretical Framework

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Abstract

Adverse conditions have been shown to have a substantial impact on traffic flow operations. It is however not yet clear to what extent emergency situations actually lead to adaptation effects in empirical longitudinal driving behavior, what the causes of these adaptation effects are and how these can best be modeled. In this paper we show using an elaborate driving simulator experiment that emergency situations lead to significant adaptation effects in longitudinal driving behavior. Furthermore we introduce a new theoretical framework. In this framework adaptation effects in longitudinal driving behavior are assumed to consist of compensation effects and performance effects. In order to empirically underpin this framework we show in this paper that compensation effects are reflected in parameter value changes in the Intelligent Driver Model, while performance effects are reflected in a reduction in model performance. Furthermore we show that compensation effects following an emergency situation are reflected in a change in the position of perceptual thresholds in a psycho-spacing model while performance effects are reflected in a reduced sensitivity of acceleration towards lead vehicle related stimuli at the action points. The paper concludes with a discussion as well as recommendations for future research.

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1. Introduction

The ability of transport systems to deal with adverse conditions has become increasingly important. Adverse conditions, in this paper defined by conditions following an unplanned event with a high impact and a low probability of occurring, have been shown to have a considerable impact in terms of economic losses, casualties, medical costs, loss of production capabilities, material and immaterial costs. Examples of adverse conditions are emergency situations (e.g., due to man-made or naturally occurring disasters), adverse weather conditions (e.g., heavy rain, thick fog, snow, black ice, etc.) and freeway incidents (e.g., vehicle crashes).

Emergency situations have been shown to have considerable impacts on traffic flow operations. For example, in the U.S. the events of the hurricanes Georges in 1998 and Floyd in 1999 precipitated the two

largest evacuations and perhaps its two largest traffic jams (Urbina & Wolshon, 2003). Hurricane Rita created substantial problems as well, as massive traffic congestion as well as fuel supply problems occurred (Litman, 2006). This revealed the fact that emergency response agencies were not as prepared for such scenarios as had been previously assumed.

However, since emergency situations have a low rate of occurring, little experience is available on how to cope with them. In order to investigate whether strategies are effective, simulation studies must be performed. For example, recently a large number of evacuation studies investigated the efficacy of evacuation strategies using well-established dynamic traffic simulation models developed for day-to-day traffic applications (Pel *et al.*, 2012). Many of these studies make use of microscopic simulation models, such as PARAMICS (Cova & Johnson, 2003), CORSIM (Williams *et al.*, 2007), VISSIM (Yuan & Han, 2009) and INTEGRATION (Mitchell & Radwan, 2006). In these microscopic simulation models mathematical models are used in order to approximate driving behavior. In order to adequately perform these studies, it is crucial that insight is available into the influence emergency situations have on empirical driving behavior as well as into the extent to which this influence is reflected in mathematical models of driving behavior.

However, insight into changes in driving behavior following an emergency situation does not inform us what the causes are of these so-called adaptation effects. Insight into the causes of these adaptation effects is crucial as this provides us with insight into how to best model the changes in driving behavior in relation to an emergency situation. To this end in this paper we introduce a new theoretical framework based on the Task-Capability-Interface model by Fuller (2005). In this theoretical framework it is assumed that emergency situations have an influence on the interaction between driver capabilities and task demands. This interaction is assumed to lead to conscious compensation effects in longitudinal driving behavior (e.g. changes in speed) and also to subconscious performance effects (e.g. reduction in the adequacy of the car-following task).

It is however not yet clear to what emergency situations actually lead to these changes in driving behavior. Furthermore, it is not yet clear to what extent compensation effects and performance effects in longitudinal driving behavior following an emergency situation are adequately represented in current car-following models.

In this paper, we therefore present extensive empirical analyses of driving behavior in case of an emergency situation using a driving simulator experiment with a multi-factorial design. We will show that emergency situations have a significant and substantial effect on empirical longitudinal driving behavior, reflected in changes in speed and distance to the lead vehicle.

In this context, in this paper we will show that emergency situations lead to substantial parameter value changes and model performance of an often used car-following model, i.e., the Intelligent Driver Model (Treiber *et al.*, 2000). In the IDM (Treiber *et al.*, 2000) acceleration is a continuous function of relative speed Δv (speed difference with the lead vehicle) and spacing s (following distance). In this paper we argue that parameter value changes in the IDM can be assumed be the result of the aforementioned compensation effects in longitudinal driving behavior following the emergency situation, while the change in model performance is argued to be an indicator for the presence of performance effects. We also argue that current continuous car-following models are less adequate in describing and predicting adaptation effects in longitudinal driving behavior due to the fact that human factors (i.e., changes in perception due to perceptual distortion, situational awareness, mental workload) are insufficiently incorporated in these models.

In order to correct for the fact that perception is not incorporated in these continuous models, psycho-spacing models were developed in the past. Basically in these models longitudinal driving behavior is controlled by perceptual thresholds. These thresholds serve to delineate a relative speed - spacing (Δv , s) plane in which the driver of a following vehicle does not respond to any change in his / her dynamic conditions and would seek to maintain a constant acceleration (Brackstone *et al.*, 2002). On crossing one of these thresholds, a driver will perceive that an unacceptable situation has occurred and will adjust his longitudinal driving behavior through a change in the sign of his acceleration. In the remainder of this paper these points in the relative speed - spacing (Δv , s) plane are referred to as 'action points'.

It is however unclear to what extent compensation and performance effects in longitudinal driving behavior following an emergency situation are represented in changes in the position of the perceptual thresholds, reflected in the position of action points in the relative speed - spacing (Δv , s) plane, as well as to what extent

the sensitivity of acceleration a towards relative speed Δv and spacing s at the action points is affected by this adverse condition. In this paper we show that compensation and performance effects following this adverse condition are substantially reflected in the position of the action points in the relative speed - spacing ($\Delta v, s$) plane and the sensitivity of acceleration towards lead vehicle related stimuli at these action points.

In sum, the objective of this paper is to empirically underpin the proposed theoretical framework through showing the effect emergency situations have on:

- empirical longitudinal driving behavior;
- parameter values and model performance of the IDM (Treiber *et al.*, 2000);
- the position and shape of the perceptual thresholds and sensitivity of acceleration a towards relative speed Δv and spacing s in psycho-spacing models.

In the next section the state-of-the-art is presented. In this section we present an overview of performed research on the structure of the driving task and the influence of emergency situations on empirical longitudinal driving behavior. This subsection is followed by an overview of mathematical modeling of longitudinal driving behavior in relation to emergency situations. The section is concluded with an overview of the available theoretical frameworks of behavioral adaptation.

In the following section we present the theoretical framework based on the Task-Capability-Interface model (Fuller, 2005). The introduction of the theoretical framework is followed by a presentation of the research method. In this section we present the research questions, describe the design of the driving simulator experiment, the developed driving environment, the research sample and the data analysis method. This section is followed by a presentation of the results. In this section we present the results with regard to the effect of an emergency situation on empirical longitudinal driving behavior, parameter values and model performance of the IDM (Treiber *et al.*, 2000) and on the position of action points and acceleration at the action points in a psycho-spacing model. In these sections the results are elaborately related to the proposed theoretical framework. The paper is concluded with a discussion section and recommendations for future research.

2. State-of-the-art

2.1. Empirical longitudinal driving behavior in relation to emergency situations

In this section we discuss the available research on the influence of emergency situations on empirical longitudinal driving behavior. However, before doing so, more insight into the structure of the driving task is needed. To this end in the next subsection we present various classifications of the driving task.

2.1.1. The structure of the driving task

With regard to the structure of the driving task Michon (1985) made a distinction between a strategic, a maneuvering and a control level. In this hierarchical control model the strategic level consists of the general planning stage of a trip, including the selection of a destination, route choice, mode choice plus an evaluation of the costs and risks involved. At the maneuvering level however, drivers exercise maneuvers allowing them to negotiate the directly prevailing circumstances. This incorporates actions as obstacle avoidance, gap acceptance, lane changing, turning and overtaking. Finally, the control level incorporates automatic action patterns (e.g., pressing the braking pedal).

These levels are hierarchical as they are assumed to influence each other in a top-down manner. However, it has also been suggested that not only top-down influences can be observed (e.g., Schaap *et al.*, 2008). For example, a closed lane may force drivers to make changes on a strategic level.

Following this hierarchical model of driving behavior, Hoedemaeker (1999) distinguished between an action-based and a task-based categorization of the driving task. The action-based categorization (Minderhoud, 1999) distinguished between a navigation subtask, a maneuvering subtask and a control subtask. While in the navigation task drivers prepare their journey, in the maneuvering task they interact with other

traffic as well as with the road system. With regard to the control task, drivers perform the elementary tasks that enable them to maneuver the vehicle safely and efficiently (Janssen *et al.*, 1992).

The task-based categorization distinguishes between roadway subtasks as well as vehicle interaction subtasks Hoedemaeker (1999). The former consists of decisions of drivers regarding the guidance of the vehicle over the available infrastructure in a proper and comfortable manner, while the latter refers to the decisions of drivers necessary to guide the vehicle around other traffic.

With regard to the vehicle interaction subtask, longitudinal as well as lateral vehicle interaction subtasks can be distinguished. Longitudinal vehicle interaction subtasks consist of acceleration, deceleration, synchronization of the speed with the speed of the lead vehicle and maintaining a desired distance from the lead vehicle, while lateral vehicle interaction subtasks consist of lane changing, merging and overtaking. Longitudinal vehicle interaction subtasks have been shown to play a substantial role in the formation and propagation of congestion. With regard to this task two different regimes can be observed:

- free flow;
- congested driving.

In the free-flow regime, the vehicle of the driver is not restricted by the presence of other traffic. In this case acceleration of the driver-vehicle combination is mainly determined by desired speed. In congested driving, the vehicle of the driver however is restricted by the presence of other traffic. In other words: there is to a certain extent hindrance from other vehicles. Here, acceleration of the driver-vehicle combination is determined by the prevailing speed, the presence of the lead vehicle(s), the speed of the lead vehicle, acceleration of the lead vehicle and net distance from the lead vehicle. When studying congestion, unconstrained driving (free-flow) is less important.

As longitudinal vehicle interaction subtasks have been shown to play a substantial role in the formation and propagation of congestion and as unconstrained driving has been shown to be less important in studying these traffic flow phenomena, this paper primarily focuses on car-following behavior in case of emergency situations.

2.1.2. Empirical driving behavior in case of emergency situations

Research on the influence of emergency situations on longitudinal driving behavior was not yet available. However, in a number of evacuation studies using microscopic simulation models, model parameters describing car-following behavior have been adjusted for emergency situations.

In research reported in Tu *et al.* (2010) it was for example assumed that drivers during an emergency situation express anxious behavior due to a mentally demanding situation. Tu *et al.* (2010) subscribe to the assumptions made in Hamdar and Mahmassani (2008). In their research it is assumed that driving behavior under emergency situations ('extreme conditions') is characterized by an aggressive driving style. Based on this assumption, they hypothesize that longitudinal driving behavior under emergency conditions is characterized by:

- an increase in speed together with higher acceleration and deceleration rates;
- a high variance in speed;
- a decrease in spacing in order to force drivers to accelerate or move out of the way;
- an increase in emergency braking and rubbernecking;
- an increase in the intensity with regard to speed and braking rates over time.

From the aforementioned it can be concluded that research on empirical adaptation effects in longitudinal driving behavior is not available. The available research is solely based on the assumption that in case of emergency situations drivers will express anxious or aggressive behavior, leading to substantial adaptation effects in driving behavior.

2.2. Mathematical modeling of longitudinal driving behavior in relation to emergency situations

2.2.1. An introduction into car-following modeling

Car-following can be regarded as a subtask of the longitudinal vehicle interaction task. This vehicle interaction subtask has received a lot of attention in the traffic flow community. Several mathematical microscopic models have been developed aiming to mimic driving behavior under a wide range of conditions and to use them in microscopic simulation as well as to guide the design of advanced vehicle control and safety systems (Brackstone & McDonald, 1999).

These models are called microscopic as they capture traffic flow at the level of individual vehicles. They describe traffic flow through behavioral rules of individual vehicles. Therefore they are by definition built on driving behavior specifications (Boer, 1999). Research has been performed as to the influence of characteristics of vehicles, characteristics of the road, driver characteristics, external conditions and traffic regulations.

In most continuous car-following models, acceleration a at time t is dependent on speed of the vehicle v , reaction time τ , relative speed Δv and spacing s :

$$a_i(t) = f_{cf}(v, \tau, \Delta v, s) \quad (1)$$

Each mathematical model of car-following has its own distinct control objective. For example, the model formulated by Gipps (1981) assumes that drivers want to reach a safe distance to the lead vehicle, while in the model formulated by Tampere (2004) it is assumed that drivers want to attain a desired distance to the lead vehicle and also want to synchronize their speed with the speed of the lead vehicle. Therefore the emphasis on the aforementioned determinants of car-following behavior differs substantially between models.

The GHR model (Gazis *et al.*, 1963) is perhaps the most well-known stimulus-response model and dates from the late fifties and early sixties. The model is expressed in the following equation:

$$a(t) = cv^m(t) \frac{\Delta v(t - \tau)}{\Delta x^l(t - \tau)} \quad (2)$$

In Eq. 2 a is the acceleration of a vehicle implemented at time t and is proportional to speed v , relative speed Δv and relative distance to the lead vehicle Δx assessed at an earlier time $t - \tau$. In this equation therefore τ represents the reaction time of the driver. Furthermore in this equation m , l and c are the parameters to be determined. As acceleration a is dependent on relative speed Δv and relative distance Δx , this model can be qualified as a stimulus-response model.

An alternative approach was taken by Treiber *et al.* (2000). Their Intelligent Driver Model (IDM) was developed as the models developed up to this point had unrealistically small acceleration and deceleration times (e.g., in case of Bando *et al.* and because the more high fidelity models like the Wiedemann model (Leutzbach & Wiedemann, 1986) have too many parameters. Furthermore, Treiber *et al.* (2000) conjectured that most models do not adequately incorporate traffic flow phenomena, such as traffic instabilities and hysteresis.

Acceleration in the IDM (Treiber *et al.*, 2000) is a continuous function incorporating different driving models for all speeds in freeway traffic as well as city traffic (Kesting *et al.*, 2010). Besides the following distance Δx and speed v the IDM also takes relative speed Δv into account. The IDM acceleration is given by:

$$a(t) = a_{max} \left[1 - \left(\frac{v(t)}{v_0} \right)^\delta - \left(\frac{s^*(v(t), \Delta v(t))}{\Delta x(t)} \right)^2 \right] \quad (3)$$

$$s^*(v(t), \Delta v(t)) = s_0 + v(t)T + \frac{v(t)\Delta v(t)}{2\sqrt{a_{max}b_{max}}} \quad (4)$$

The expression combines a free flow acceleration regime $a[1 - (v/v_0)^\delta]$ with a deceleration strategy $-a(s^*/\Delta x)^2$. The latter becomes relevant when the distance to the lead vehicle Δx is not significantly larger than the desired distance to the lead vehicle s^* .

The free flow acceleration is characterized by free speed v_0 , maximum acceleration a_{max} and the component δ . The component δ characterizes how acceleration decreases with speed.

The desired distance to the lead vehicle s^* is composed of a minimal stopping distance ('jam distance') s_0 , and a speed dependent distance vT . This corresponds to following the lead vehicle with a constant desired time headway T and a dynamic contribution which is only active in non-stationary traffic conditions. This implements an 'intelligent' driving behavior that, in normal situations, limits braking decelerations to the maximum deceleration b_{max} (Kesting *et al.*, 2010). The aforementioned stimulus response models therefore in various ways have tried to describe acceleration of a following vehicle. These models however have some important drawbacks, e.g.:

- only the behavior of the direct lead vehicle is incorporated in the models;
- the only human element is a finite reaction time, other human elements are rather mechanistic (e.g., influence of mental workload and perceptual narrowing);
- drivers are assumed to react to small changes in relative speed even though headways are substantial;
- drivers are assumed to perceive stimuli no matter how small;
- situations are adequately evaluated and adequate responses are executed;
- the gas and brake pedals are operated in a precise manner. Errors made in operating the pedals are not taken into account;
- drivers do not want to permanently be occupied with the car-following task.

One of the drawbacks that was mentioned is the fact that drivers are assumed to react to small changes in relative speed, even at larger headways. This was adjusted for in so-called psycho-spacing models (Leutzbach & Wiedemann, 1986) through the introduction of perceptual thresholds. Michaels (1963) provided the basis for the first psycho-spacing model based on theories borrowed from perceptual psychology. In these models, car-following behavior is described on a relative speed - spacing ($\Delta v, s$) plane (see Figure 1).

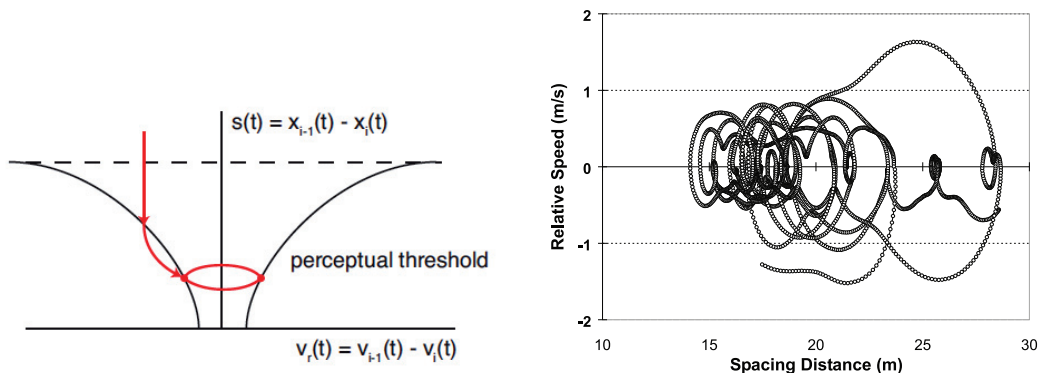


Fig. 1. A basic psycho-spacing model (Leutzbach *et al.*, (1986)) (left) and the typical 'close' following spirals (Brackstone *et al.*, 2002) (right).

In this context Brackstone *et al.* (2002) formulated four different perceptual thresholds, which they borrowed from Leutzbach & Wiedemann (1986). The first threshold is a threshold with regard to a minimum desired following distance ABX . This threshold is expressed as follows:

$$ABX(v) = AX + BX \sqrt{v} \quad (5)$$

In this equation AX denotes the minimum desired spacing when stationary (much like s_0 in the Intelligent Driver Model Treiber *et al.* (2000)). This includes the length of the vehicle. The parameter BX is the additional spacing required to account for speed. The next perceptual threshold is a threshold for a maximum desired following distance:

$$SDX(v) = AX + BX \sqrt{v} EX \quad (6)$$

This equation is similar to the one for minimum desired following distance with addition of the term EX . This parameter EX produces an increase of SDX over ABX of an additional 0.5-1.5 times the dynamic speed component Brackstone *et al.* (2002). A third perceptual threshold is a threshold for recognizing small negative (closing) relative speeds:

$$CLDV(DX) = \frac{-DX^2}{CX^2} \quad (7)$$

This equation corresponds to a threshold in the perception of the divergence of the visual angle according to the constant CX . Finally a similar threshold for small positive (opening) speeds is formulated, with the constant OP :

$$CLDV(DX) = \frac{DX^2}{OP^2} \quad (8)$$

If the vehicle crosses one of these thresholds, it will respond with a constant acceleration or deceleration, typically in the order of $0.2m/s^2$. In the remainder of this chapter this point in the $(\Delta v, s)$ plane is referred to as an 'action point'.

In this subsection we provided a brief overview of car-following modeling. In the next subsection we discuss to what extent adaptation effects in longitudinal driving behavior following an emergency situation have been modeled in the past.

2.2.2. Car-following modeling and emergency situations

As was previously mentioned, Tu *et al.* (2010) adjusted parameters in a simulation software package (i.e., PARAMICS) in order to account for aggressive or anxious driving during an emergency situation. In this context, they subscribed to the assumptions made by Hamdar and Mahmassani (2008).

Hamdar and Mahmassani (2008) took a step forward in the incorporation of adaptation effects in longitudinal driving behavior due to an emergency situation. They devised a model to capture longitudinal driving behavior under extreme conditions through modification of the safe-distance model by Gipps (1981). The authors used this model as from their research it followed that this showed an acceptable degree of stability when relaxing its safety constraints.

Hamdar and Mahmassani (2008) state that with regard to acceleration under extreme conditions, drivers are more willing to apply higher acceleration rates than under normal driving conditions, which cause irregularities and possible instabilities in traffic flow patterns. The variable a_i was drawn from a truncated Gaussian shaped distribution to deal with unrealistically high and low volumes. With regard to maximum deceleration Hamdar and Mahmassani (2008) assume that the value of this parameter can increase in absolute value, as under extreme conditions drivers tend to have higher braking rates or an increased use of emergency braking. In their modification of the Gipps model (Gipps, 1981) they also altered the variable representing desired speed. In extreme conditions the true value of this parameter was drawn from a probabilistic mixture of two Gaussian distributions in which the means are respectively higher and lower than the suggested mean in the original formulation of the model.

In the aforementioned we assumed that adaptation effects in longitudinal driving behavior following an emergency situation are characterized by conscious compensation effects and subconscious performance effects. These compensation and performance effects are assumed to follow from an interaction between task demands and driver capabilities. From the aforementioned it can be observed that these human elements are not incorporated in the discussed current models.

A step towards incorporating driver capability in car-following models was however taken in Tampère (2004), as in this model finite reaction times, anticipation and driving style variations (i.e., attention level) are explicitly incorporated. In their gas-kinetic model the general law for the conservation of probability was transformed through use of the method of moments. Through this method the following macroscopic traffic flow model was derived:

$$\frac{\partial k}{\partial t} + \frac{\partial kV}{\partial x} = \left(\frac{dk}{dt} \right)_{event} \quad (9)$$

$$\frac{\partial kV}{\partial t} + \frac{\partial (kV^2 + k\theta)}{\partial x} = k \left\langle \frac{dv}{dt} \right\rangle_v + \left(\frac{dkV}{dt} \right)_{event} \quad (10)$$

In this equations k denotes the density, V denotes the speed, while θ denotes the acceleration. Driving style variations were implemented by characterizing an individual's state not only by the individual speed v and the distance to the lead vehicle, but also by the attention level a . Again the authors use the method of moments in order to obtain the speed dynamic equation (Tampère, 2004):

$$\frac{\partial A}{\partial t} + V \frac{\partial A}{\partial x} = \left\langle \frac{da}{dt} \right\rangle_{v,a} + \frac{1}{k} \int_a \int_v a \left(\frac{d\rho}{dt} \right)_{event} dv.da - \frac{A}{k} \left(\frac{dk}{dt} \right)_{event} \quad (11)$$

In Equation 11 the first term on the right represents the effect of driver induced changes in the attention level A . The second term represents the effect due to events in the flow while the last term represent the redistribution of the total attention level A over the population k in case the density does not remain constant (Tampère, 2004).

In this subsection we discussed car-following modeling in relation to emergency situations. In this context we discussed the model proposed by Hamdar and Mahmassani (2008) as well as the model by Tampère (2004). However, both models are not based on an empirically underpinned theoretical framework of behavioral adaptation. To this end in the next subsection we provide a brief overview of often used theoretical frameworks in relation to behavioral adaptation.

2.3. Integrative theoretical frameworks of behavioral adaptation

Examples of cognitive approaches to behavioral adaptation are the Theory of Risk Homeostasis (Wilde, 1982) and the Theory of Planned Behavior (Ajzen & Madden, 1986). The Risk Homeostasis Theory (RHT) developed by Wilde (Wilde, 1982) proposes that drivers tend to target a specific level of risk, in which safety levels remain relatively constant. This theory is however not uncontested. For example, earlier Summala and Naatanen (1974) already stated that drivers try to avoid risk by regulating their behavior according to a perception of zero risk, while in Wilde (1982) it is conjectured that drivers seek a specific risk level.

However in both approaches it is assumed that risk level is a number to be defined by the level of exposure (Vaa, 2001). In literature however, no trace can be found of this weighing procedure. Tversky and Kahneman (1974) show that people put much weight into their own experiences. Tversky and Kahneman (1974) are however not referred to in Wilde (1982). Vaa (2001) concludes in this context that a target level of risk cannot be a number, a thought or imagination that is brought with you consciously and which is put into some weighing procedure when, for example, is decided at which speed should be driven. Vaa (2001) continues by stating that the RHT model does not grasp or mimic the varied dynamics of thinking and feeling.

Within the various approaches, the Theory of Planned Behavior (Ajzen & Madden, 1986) is perhaps the most often used theoretical framework. However, this framework has some drawbacks. For instance, Gabany *et al.* (1997) state that the constructs incorporated in this framework cannot reliably and valid be measured due to unclear psychometric properties of the measures used. Furthermore, the predictive power of this framework has been shown to be limited and only one conscious aspects of driving is captured.

Due to the drawbacks of these frameworks, integrative approaches have been developed, which incorporate conscious cognition as well as skill-based behavior. Perhaps the highest level of integration of personal and environmental factors was provided in the Task Capability Interface Model (Fuller, 2005). In the next

subsection we will in this context introduce an adaptation of this TCI model (Fuller, 2005) aimed at explaining adaptation effects in longitudinal driving behavior following an emergency situation.

2.4. *Introducing a theoretical framework of behavioral adaptation in longitudinal driving behavior in relation to emergency situations*

In the TCI model driving task difficulty comes forth from the dynamic interface between the demands of the driving task and the capability of the driver. Fuller (2005) mentions that driver capabilities are restricted by biological personal characteristics of the driver as well as by experience. However, these capabilities due to biological personal characteristics (e.g., age, gender, ethnicity) and driving experience alone do not determine the total temporal capabilities of the driver, as more dynamic variables play a substantial role as well. An example of a dynamic driver characteristic is activation level. Activation level is defined as the individual's degree of energy mobilization (Cannon, 1915). Another important determinant influencing driver capability is distraction. It can be assumed that in case of distraction (e.g., due to mobile telephone conversations while driving) driver capability will reduce (Brookhuis *et al.*, 1991). Driver capability is therefore influenced by many endogenous and exogenous variables. In this regard Brookhuis *et al.* (2001) assume that driver capabilities may vary between as well as within drivers.

Driving task demands are also related to a multitude of elements. Elements that may play a vital role are visibility (e.g., in case of adverse weather conditions), the complexity of the road design and interactions with other road users, etc. Important elements in task demand are however the elements over which the driver of the vehicle has direct control. These conscious actions of the driver are in the ensuing referred to as compensation effects. Here, speed of the vehicle is clearly the most significant element: the faster a driver is moving, the less time is available to perceive stimuli, process information and make decisions. As Taylor (1964) regards the driving task as self-paced, driving task demand is in a fundamental way under the control of the driver through speed selection.

Driver capabilities as well as task demands are assumed to interact. In this regard three main regions can be distinguished (Fuller, 2005):

- where driving capabilities exceed demands, the task is not difficult, or even too easy;
- when demands of the task at hand equal the capabilities of the driver, the task is difficult;
- when task demands exceed the capabilities of the driver, the driver is assumed to fail the task.

When drivers fail the driving task, a loss of control can be observed as a consequence. Thus in essence, task difficulty is inversely proportional to the difference between the task demand and the capability of the driver. According to Fuller (2005), at the threshold where task demand begins to exceed the capability of the driver, a fragmented degradation of the driving task is to be expected. Fuller (2005) continues by stating that with a static level of capability, any event that increases task demand will therefore reduce this critical difference, increase task difficulty and potentially influence driving task performance.

In the proposed theoretical framework (see Figure 2) emergency situations have an influence on dynamic driver characteristics. In this context it is for example easy to imagine that when the level of urgency following an emergency situation increases, the activation level of the drivers will also increase. In this sense, drivers can be assumed to experience arousal due to the time pressure they experience with regard to evacuating the location in time. This increase in activation level is assumed to lead to an increase in driver capability.

Furthermore, we assume that emergency situations will have an influence on task demands. The emergency situation will presumably have an influence on factors such as traffic intensity, visibility, etc. The change in task demands and driver capability leads to an imbalance. In order to correct for this imbalance in task difficulty, a driver will show compensatory behavior by influencing task demand. For example, in case of emergency situations drivers will increase their speed in order to increase task demand.

However, when this compensatory behavior of the drivers is not sufficient to restore a situation of homeostasis, performance effects in longitudinal driving behavior may be observed. It can for example be assumed that drivers will follow the lead vehicle less adequately. In other words: a reduction in the performance of the car-following task may be the result.

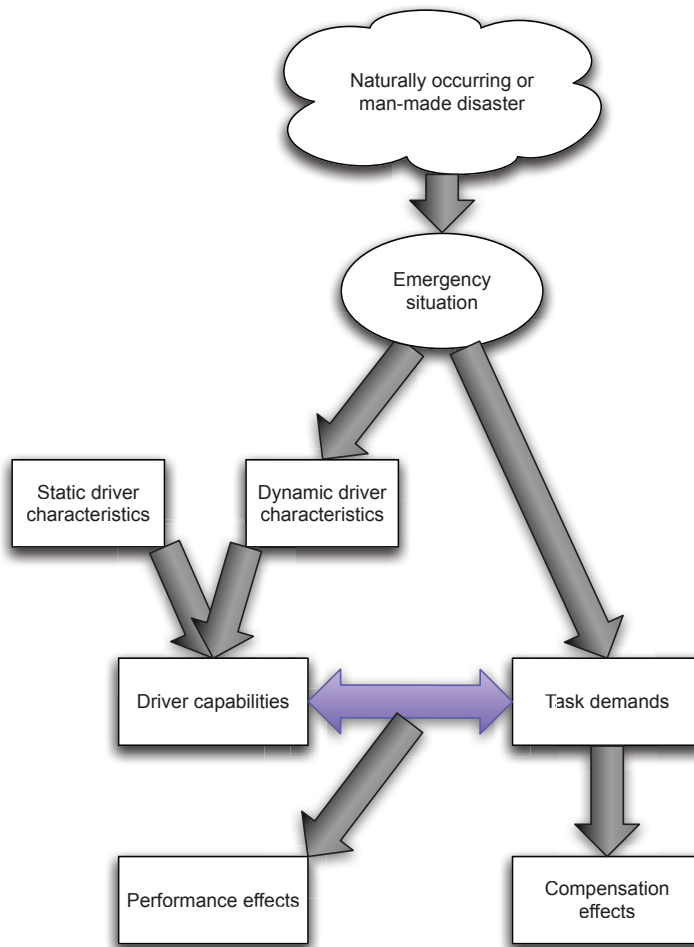


Fig. 2. Theoretical framework connecting emergency situations to compensation and performance effects in longitudinal driving behavior.

In the present section we discussed the structure of the driving task, followed by a brief overview of the available research on the influence of emergency situations on empirical longitudinal driving behavior. We showed that no research was available on the actual changes in longitudinal driving behavior following an emergency situation. Next we provided an overview of current car-following models. In this context an in-depth discussion of the Intelligent Driver Model (Treiber *et al.*, 2000) and psycho-spacing models

was presented (Leutzbach & Wiedemann, 1986). This subsection was followed by a brief overview of car-following models in relation to emergency situations. We argued that most mathematical car-following models insufficiently incorporate human elements and are not based on an empirically underpinned theoretical framework of behavioral adaptation. To this end we discussed several theoretical frameworks of behavioral adaptation and introduced a theoretical framework aimed at explaining adaptation effects in longitudinal driving behavior following an emergency situation based on the TCI model (Fuller, 2005).

In order to empirically underpin the proposed theoretical framework insight is needed into the extent to which compensation and performance effects can actually be observed in case of an emergency situation. To this end in the next section the research method is presented aimed at determining changes compensation and performance effects on longitudinal driving behavior.

3. Research Method

In this section we present the research method. We start with a presentation of the research questions, followed by a description of the experimental design. Next we provide an introduction into the driving simulator owned by Delft University of Technology, Civil Engineering and Geosciences, Transport and Planning and present the driving environment developed for the purpose of this experiment. This section is followed by a description of the research sample and the data analysis method.

3.1. Research questions

In the proposed theoretical framework we assume that adaptation effects in longitudinal driving behavior following an emergency situation consist of conscious adaptation effects (changes in for example speed in order to change task demands) and performance effects (e.g., a change in the performance of the car-following task). However, it followed from the state-of-the-art in the previous section that it is not yet clear to what extent emergency situations actually lead to adaptation effects in empirical longitudinal driving behavior. Therefore the first research question is:

- To what extent do emergency situations influence empirical longitudinal driving behavior, reflected in changes in speed v , acceleration a , deceleration b , spacing s and relative speed Δv ?

In this paper we assume that conscious compensation effects are reflected in parameter value changes. In the context of the IDM (Treiber *et al.*, 2000) we therefore assume that emergency situations will lead to substantial changes in maximum acceleration a_{max} , maximum deceleration b_{max} , free speed v_0 and desired time headway T . In this context the second research question is:

- To what extent are compensation effects in longitudinal driving behavior following an emergency situation reflected in changes in maximum acceleration a_{max} , maximum deceleration b_{max} , free speed v_0 and desired time headway T in the Intelligent Driver Model (Treiber *et al.*, 2000)?

Furthermore it can be assumed that performance effects in longitudinal driving behavior following an emergency situation are reflected in the adequacy of the car-following task. This may be reflected in changes in the performance of the car-following model in question. It is however not yet clear to what extent emergency situations actually lead to a change in the performance of the Intelligent Driver Model (Treiber *et al.*, 2000). Therefore the third research question is:

- To what extent are performance effects in longitudinal driving behavior following an emergency situation reflected in changes in performance in the Intelligent Driver Model (Treiber *et al.*, 2000)?

It can be argued that these changes in model performance of continuous car-following models (i.e., the IDM (Treiber *et al.*, 2000)), may be a result of the fact that human elements are insufficiently incorporated in current car-following models. In order to adjust for this psycho-spacing models (Leutzbach & Wiedemann, 1986) were developed. As was mentioned before, in these models perceptual thresholds are incorporated.

One way in which compensation effects following an emergency situation are reflected in longitudinal driving behavior is through these perceptual thresholds, as these thresholds determine at which relative speeds and spacing drivers react with a change in their acceleration. It is however not yet clear to what extent compensation effects in longitudinal driving behavior following an emergency situation are actually reflected in changes in the position of perceptual thresholds in psycho-spacing models (Leutzbach & Wiedemann, 1986) represented by the position of action points in the relative speed - spacing (Δv , s) plane. Therefore the fourth research question is:

- To what extent are compensation effects following emergency situations reflected in the position of action points the relative speed - spacing (Δv , s) plane in a psycho-spacing model?

Finally, it can be assumed that performance effects in longitudinal driving behavior following an emergency situation are reflected in the sensitivity of acceleration a towards relative speed Δv and spacing s at the action points in a psycho-spacing model. It is however not yet clear to what extent emergency situations actually influence the sensitivity of acceleration a towards these lead vehicle related stimuli. Therefore the fifth research question is:

- To what extent are performance effects following emergency situations reflected in the sensitivity towards relative speed Δv and spacing s at action points in a psycho-spacing model?

In this subsection we presented the research questions needed in order to empirically underpin the proposed theoretical framework based on the Task-Capability-Interface model but Fuller (2005). In the next subsections we describe the research method used in order to answer the research questions. We start with a presentation of the experimental design.

3.2. *Experimental design*

In the driving simulator experiment, participants were randomly divided into two groups: a control group and an experimental group. In the experiment between subjects factors as well as within subject factors were distinguished, rendering up a complete multifactorial design. A multi factorial design allows for the analysis of effects between groups as well as of effects within participants. As a between subjects factor the factor Urgency was introduced. This between subjects factor consisted of the induction of a sense of urgency within the participants in the experimental group. In the control group no sense of urgency was induced.

This induction of a sense of urgency within the participants in the experimental group was achieved by communicating to these participants that they would receive a maximum reward of EUR 30,- under the condition that they would safely reach their destination in time. For every time unit the participants in the experimental group were late they would receive an equally smaller reward. In the control group it was communicated to the participants that they would receive a reward of EUR 20,-, regardless whether they would reach their destination in time.

As a within subject factor, the factor Time (3) was implemented. To achieve this the test drive in the driving simulator was divided into three segments of equal duration. This was done in the experimental group as well as in the control group. During the experiment longitudinal driving behavior was measured in both groups and all conditions. More details on this within subject factor are provided in the next subsection.

3.3. *The driving simulator and validity issues*

The fixed base driving simulator consists of three screens placed at an angle of 120 degrees, a driver's seat mock-up and hardware and software interfacing of this mock-up to a central computer system (Figure 3). From the driver's seat the view consists of a projection of 210 degrees horizontally and 45 degrees vertically. The software was developed by STSoftware.

Driving simulators possess a large degree of controllability. A possible disadvantage is that driving simulators only provide a representation of reality and not reality itself. The high degree of experimental control is accompanied by a reduction in validity. Validity can be defined as the extent to which the data collection method serves its purpose.



Fig. 3. Fixed base Driving Simulator

Jamson (2000) made, in this context, a distinction between behavioral and physical validity of driving simulators. The first refers to the ability of the driving simulator to induce the same behavioral response from drivers as in real life. The latter refers to the extent in which dynamics and the visual system of a driving simulator produces an experience which resembles real life.

Kaptein *et al.* (1996) made distinctions between absolute, relative, internal and external validity. Absolute validity can be defined as the extent in which an effect during a certain task in the driving simulator can be compared to real life. For absolute validity to be present, the direction as well as the magnitude of the reaction has to be similar to real life reactions. Relative validity can be defined as the extent to which a comparable trend can be observed in the driving simulator as is the case in real life. For a driving simulator to possess relative validity, it is not required that the magnitude of the behavioral response is the same.

Several validation studies have been performed on the driving simulator used in the research reported in this paper. In research conducted by Blaauw (1982) absolute and relative validity was evaluated in terms of system performance and driver behavior for inexperienced and experienced drivers. These participants had to perform lateral and longitudinal vehicle control both in the simulator and in an instrumented car on the road. Task demands for each control were varied with a free and forced accuracy instruction. Overall results showed good absolute and relative validity for longitudinal vehicle control, while lateral vehicle control offered good relative validity. Lateral control performance lacked absolute validity due to the drivers' diminished perception of lateral translations. Performance in the simulator was a more sensitive discriminator of driving experience than was performance in the instrumented car on the road. Another study conducted with this fixed-base driving simulator evaluated the available visual information in order to determine which information is crucial in executing tasks by the driver (Kaptein *et al.*, 1996). They performed two driving simulator experiments. The results were compared with real life data. When approaching a stationary vehicle, subjects were instructed to brake as late as possible, without causing a collision. The instruction was either to brake hard or to brake normal. The first experiment showed that the timing of the start of the braking maneuver was not affected by field of view and scene complexity. Yet, the coordination of the ongoing braking maneuver was more realistic with increasing field of view. The results show that drivers took larger safety margins with higher approach speeds. In the second experiment in 50% of the trials the image was occluded immediately after the onset of the braking maneuver. Results showed that without visual information during the braking maneuver, drivers tended to exceed the intended stopping position more often. The results confirmed the relative validity of the driving simulator and stressed the importance of the presence of sufficient visual information.

Also recent research has confirmed the relative validity of driving simulators. For instance, Lee (2003) found that performance of a low cost driving simulator could explain more than two-thirds of the variance in 'on the road' assessments in elderly drivers. Also recent research conducted by Yan *et al.* (2008) showed that driving simulators have relative validity. In their experiment differences between behavior in the driving simulator and real life at crossroads was investigated. Finally in Bella (2008) a study was performed on the interactive fixed base driving simulator of the Inter-University Research Center for Road Safety (CRISS). This study was conducted in order to verify whether driving simulators are a useful tool for speed research on two lane rural roads. The statistical analyses established the relative validity and also revealed the absolute validity in nine out of eleven measurement sites. Only in two non-demanding configurations speeds were significantly higher than those recorded in real life.

The aforementioned shows clearly that in general driving simulators possess relative validity. However, a validation study with regard to empirical longitudinal driving behavior in case of an emergency situation using the Advanced Driving Simulator has not yet been performed.

3.4. The driving environment

For the purpose of the experiment, a driving environment was developed consisting of four segments. The first segment consisted of a short test drive through a suburban area to accustom participants to driving in a driving simulator and also to investigate whether the participants were prone to simulator sickness (Figure 4). The other three segments were used in the experiment. These test trials took place on a virtual motorway with two lanes in the same direction. No speed limit was set. The length of the four segments combined was 18.9 km.

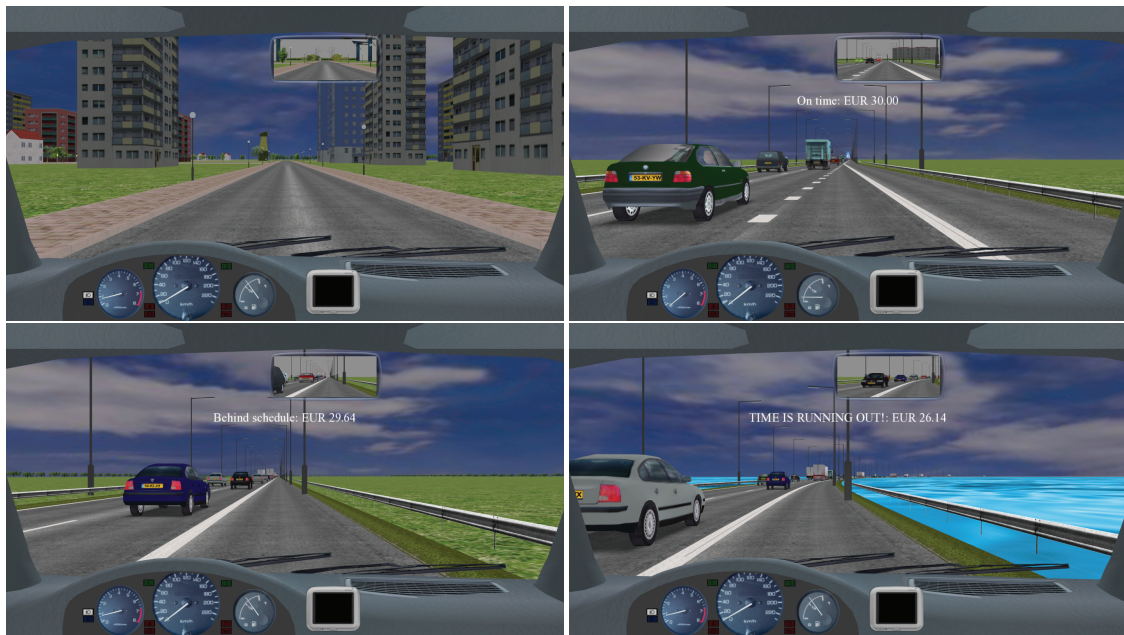


Fig. 4. Test drive suburban area (top left), the On Time condition (top right), the Behind Schedule condition (bottom left) and the Out of Time condition (bottom right)

Between the three segments used in the experiment the level of urgency was varied in the experimental group. The variation in this level of urgency was achieved by exposing the participants to messages on the screen regarding the extent in which they still performed in accordance with the preset time limit. Due to the increasing nature of the level of urgency, typical of an emergency situation, no counterbalancing across subjects was applied.

In the first segment the participants received the message on-screen that they were still on time (Figure 4). In this message also the remaining reward (EUR 30,-) was communicated to the participants. In the

ensuing will be referred to this condition as the 'On Time' condition. In the second segment the participants in the experimental group received the message that they were behind schedule. At the same time the remaining reward started to decrease. In the remainder this segment will be referred to as the 'Behind Schedule' condition. Finally, in the third segment the participants in the experimental group received the message that time was running out. At the same time the remaining reward started to decrease even faster. In order to enforce the sense of urgency flooding of the environment was simulated. In the ensuing this condition will be referred to as the 'Out of Time' condition.

In the control group the participants drove the same route as the participants in the experimental group. However, they did not receive the messages discussed earlier. Also, flooding was not simulated in the 'Out of Time' condition. In both groups behavior of the other road users was similar. In both groups moderately congested traffic conditions were simulated as well as two stop-and-go traffic conditions.

3.5. Measures and participants

Longitudinal driving behavior, represented by speed, speed of the lead vehicle, acceleration, deceleration and spacing, were measured through registered behavior in the driving simulator at a sampling rate of 10 samples per second. The research population consisted of 38 employees and students of Delft University of Technology (21 male and 17 female participants). The age of the participants varied from 21 to 56 years with a mean age of 30.41 years ($SD = 5.30$). Driving experience varied from 3 to 29 years with a mean of 10.31 years ($SD = 6.41$).

3.6. Data analysis methods

First, descriptive statistics were calculated for speed v , acceleration a , deceleration b , relative speed Δv and spacing s . For Δv a distinction was made between positive and negative values. Here, positive values represent closing relative speeds, while negative values of Δv_i represent opening relative speeds.

To analyze whether the observed effects in the descriptive statistics with regard to longitudinal driving behavior were significant, a Multivariate Analysis of Variance (MANOVA) was performed. A MANOVA is a generalized form of univariate analysis of variance (ANOVA). Analogous to ANOVA, MANOVA is based on the product of model variance matrix Σ_{model} and inverse of the error variance matrix Σ_{res}^{-1} or $A = \Sigma_{model} * \Sigma_{res}^{-1}$. This statistical technique allows for the analysis of main effects as well as the analysis of interaction effects fort within subject as well as between subject factors.

In order to test for within and between subjects effects, longitudinal driving behavior (consisting of the measurements of v , a , Δv and s) were transformed into linear and quadratic trend contrast scores by means of computation of orthogonal polynomials (Tabachnick & Fidell, 2001). The analysis was applied to these contrast scores, which were chosen a priori for the control group as well as the experimental group with Time (3) as a within subjects factor and Urgency (2) as a between subjects factor.

Here Time (3) consisted of the three conditions, respectively the 'On Time', 'Behind Schedule' and 'Out of Time' condition. The factor Urgency (2) consisted of the two groups, respectively the control group and the experimental group. In this regard, Mauchly's test of Sphericity was performed in order to test for homogeneity of variances. If this assumption was violated, degrees of freedom were corrected using the Greenhouse-Geisser estimates of sphericity. In case of significant interactions of contrast scores with Urgency (2), testing of simple post-hoc contrast scores was performed. Due to the a priori character of the tests, they were performed with the conventional Type I error of .05.

Parameter value changes and model performance of the Intelligent Driver Model (Treiber *et al.*, 2000) were determined through the approach described in Hoogendoorn and Hoogendoorn (2010). This calibration method for joint estimation is a derivation of a statistical parameter estimation approach, enabling the statistical analysis of the model estimates and cross-comparison of models of differing model complexity. The approach allows using multiple trajectories simultaneously, through which the estimation results are improved when the information in individual trajectories is limited. Also the approach allows for the inclusion of prior information on the parameter values to be estimated. The approach is elaborately described in Hoogendoorn & Hoogendoorn (2010).

In order to determine compensation effects represented by changes in the perceptual thresholds in a psycho-spacing model (Leutzbach & Wiedemann, 1986) we started with estimating action points in the

$(\Delta v, s)$ plane in a psycho-spacing model using the data filtering technique described in Hoogendoorn *et al.* (2011). The basic assumption of the applied method is that a trajectory can be represented by non- equidistant periods in which acceleration is constant. This implies that speed $v(t)$ is a continuous piecewise linear function of time. For instance, let t_j for $j = 0, \dots, M$ denote the time instants at which the acceleration changes (i.e., the action points). Given these time instants, we aim to find the points y_j describing the value of the piecewise linear function at the time instants t_j .

This provides us with a distribution of action points in the relative speed-spacing $(\Delta v, s)$ plane. These distributions were compared using a Kolmogorov-Smirnov test with a significance level of .05. Also, in order to be able to compare the perceptual thresholds we aimed finding the coefficients of the polynomials $p(x)$ that fitted the action points $p(x(i))$ to $y(i)$ in a least squares sense:

$$p(x) = p_1 x^3 + p_2 x^2 + p_3 \quad (12)$$

This analysis was performed separately for acceleration reductions and acceleration increases at the action points. The goodness of fit, which is regarded as an indication for the degree of within and between driver heterogeneity was determined through calculation of the Mean Squared Error (MSE).

In order to determine changes in the sensitivity of acceleration a towards lead vehicle related stimuli at the action points following a change in complexity of the driving task, a Multivariate Regression Analysis was performed. In this analysis the following model was fitted, as this model showed the best possible fit to the data:

$$a = b_1 \frac{\Delta v}{\sqrt{s}} + b_2 \Delta v \quad (13)$$

This relation assumes that the acceleration a is a linear function of relative speed Δv , which implies that the larger Δv , the larger the chosen acceleration. Furthermore, the model shows that the magnitude of acceleration at the action points reduces for larger values of s . Note that this relation does not describe whether a driver will accelerate or not. Instead, it describes the (average) acceleration the driver chooses to accelerate at a certain value of Δv and s .

In the present section we introduced the research questions as well as presented the research method used to answer these questions. In the next section we present the results of the driving simulator experiment. In this context, we start with a presentation of the results with regard to the influence of emergency situations on empirical longitudinal driving behavior.

4. Results

4.1. Adaptation effects in empirical longitudinal driving behavior

As was previously mentioned, we assume in the theoretical framework that adaptation effects in longitudinal driving behavior following an emergency situation consist of compensation and performance effects. However, we argued that the extent in which adaptation effects in empirical longitudinal driving behavior following an emergency situation can be observed was not yet clear. The first research question was therefore: "To what extent do emergency situations influence empirical longitudinal driving behavior, reflected in changes in speed v , acceleration a , deceleration b , spacing s and relative speed Δv ?"

Table 1 shows the mean values and the standard deviations (between brackets) of speed v , acceleration a , deceleration b , spacing s and positive and negative relative speed Δv_{pos} and Δv_{neg} for the data collected in the emergency situation experiment. It does so for the control and for the experimental group, as well as for the different experimental conditions ('On time', 'Behind schedule' and 'Out of time').

From the table it can be observed that mean values of speed v in the control group differ substantially from mean values in the experimental group. Furthermore, in contrast with the control group, mean values of speed v differ substantially between the three conditions in the experimental group.

In the 'On Time' condition mean speed v is lower than in the 'Behind Schedule' condition, while mean speed v in the 'Out of Time condition' is larger than in the other two conditions. Furthermore, it can be

observed from the table that in the experimental group standard deviations are substantially larger than in the control group.

A similar picture emerges for acceleration a and deceleration b . Overall, differences can be observed between the mean values of acceleration a and deceleration b in the control group and in the experimental group. The table shows that especially acceleration a is larger in the experimental group than in the control group. Mean values as well as standard deviations for the control group are quite similar between the three conditions. This is in contrast with the mean values and standard deviations in the experimental group, as here substantial differences in mean values and standard deviations of acceleration a can be observed.

From the table it can be also observed that when comparing the three conditions in the control group, the mean value of spacing s is larger in the 'On Time' condition compared to the 'Behind Schedule' condition and the 'Out of Time' condition. The difference in mean values between the 'Behind Schedule' and the 'Out of Time' condition is not substantial. Furthermore, it can be observed from the table that mean values of spacing s in the experimental group differ substantially from the control group. Also overall, standard deviations are smaller in the experimental group.

Table 1. Mean and standard deviation of speed (v), acceleration (a), deceleration (b), spacing (s), positive relative speed (Δv_{pos}) and negative relative speed (Δv_{neg}) for the control group and the experimental group per condition.

	speed (km/h)	acceleration (m/s^2)	deceleration (m/s^2)
<i>Control</i>			
On Time	86.38(11.58)	.41(.37)	-.43(.90)
Behind Schedule	84.45(4.87)	.38(.54)	-.63(.86)
Out of Time	83.05(9.15)	.35(.34)	-.50(.66)
<i>Experimental</i>			
On Time	92.85(17.81)	.56(.98)	-.74(.96)
Behind Schedule	110.45(23.83)	.59(1.03)	-.75(1.01)
Out of Time	117.06(19.60)	.83(1.36)	-.97(1.20)
	spacing (m)	pos. relspeed (km/h)	neg. relspeed (km/h)
<i>Control</i>			
On Time	45.53(55.71)	3.11(3.12)	-3.08(3.13)
Behind Schedule	38.62(67.00)	1.77(2.01)	-3.21(3.04)
Out of Time	39.01(31.25)	.97(1.29)	-3.02(2.97)
<i>Experimental</i>			
On Time	27.98(43.91)	1.09(1.59)	-2.80(3.71)
Behind Schedule	24.74(38.93)	.63(.85)	-2.38(3.34)
Out of Time	21.42(31.93)	.78(1.65)	-2.13(3.98)

For positive relative speed Δv_{pos} the table shows that mean values as well as standard deviations for the control group differ substantially between the three conditions. However, mean values of positive relative speed Δv_{pos} in the experimental group are smaller than in the control group, while standard deviations in the control group are larger than in the experimental group. Furthermore, it can be observed from the table that mean values as well as standard deviations of positive relative speed Δv_{pos} in the experimental group differ substantially between the three conditions. In the 'On Time' condition mean positive relative speed Δv_{pos} is substantially larger than in the 'Behind Schedule' and 'Out of Time' condition. The difference between the 'Behind Schedule' and the 'Out of Time' condition is less substantial.

Finally, it can be observed that mean values as well as standard deviations of negative relative speed Δv_{neg} for the control group do not substantially differ between the three conditions. It can however also be observed that on average mean values of negative relative speed Δv_{neg} in the experimental group are larger than in the control group. Furthermore on average standard deviations in the experimental group are larger. It can also be observed that mean values of negative relative speed Δv_{neg} differ substantially between the three conditions in the experimental group. When comparing these three conditions it becomes clear that

mean negative relative speed Δv_{neg} is smaller in the 'On Time' condition compared to the 'Behind Schedule' condition. Furthermore the table shows that the mean value of negative relative speed Δv_{neg} in the 'Behind Schedule' condition is smaller than in the 'Out of Time' condition.

In summary, the descriptive statistics indicate substantial adaptation effects in empirical longitudinal driving behavior. In the experimental condition a substantial increase in speed v , acceleration a , deceleration b can be observed along with small distances to the lead vehicle s . Furthermore, the drivers seem to follow the lead vehicles more closely, as indicated by smaller positive and negative relative speeds Δv . From the descriptive statistics it can be concluded that in case of an emergency situation drivers seem to drive faster with stronger accelerations and decelerations as well as at smaller following distances.

The aforementioned is supported by the results of the MANOVA in Table 2. In the table F-values, the degrees of freedom (df), as well as the error and the p-value is displayed for speed v , acceleration a , deceleration b , spacing s , positive relative speed Δv_{pos} and negative relative speed Δv_{neg} .

Table 2. Results Multivariate Analysis of Variance for empirical adaptation effects in longitudinal driving behavior under emerging situations / evacuations.

Variable	Factor	Pillai's T	F	df	Error	p
Speed v	Urgency(2)	-	39.53	1	38	.00
	Time(3)	.29	8.30	2	76	.00
	Urgency(2) x Time(3)	.34	10.39	2	76	.00
Acceleration a	Urgency(2)	-	5.24	1	38	.02
	Time(3)	.06	1.48	2	76	.23
	Urgency(2) x Time(3)	.07	1.74	2	76	.18
Deceleration b	Urgency(2)	-	1.63	1	38	.24
	Time(3)	.05	.99	2	76	.37
	Urgency(2) x Time(3)	.02	.32	2	76	.72
Spacing s	Urgency(2)	-	34.94	1	38	.00
	Time(3)	.33	9.41	2	76	.00
	Urgency(2) x Time(3)	.29	12.94	2	76	.00
Positive relspeed Δv_{pos}	Urgency(2)	-	17.80	1	38	.00
	Time(3)	.22	6.19	2	76	.00
	Urgency(2) x Time(3)	.23	6.20	2	76	.00
Negative relspeed Δv_{neg}	Urgency(2)	-	9.02	1	38	.00
	Time(3)	.16	4.12	2	76	.00
	Urgency(2) x Time(3)	.14	5.11	2	76	.00

Here, the F-value is defined as the between groups mean squares divided by the mean squares of error. The F-ratio is therefore the product of two ratios. The first ratio is the degrees of freedom for error divided by the between groups degrees of freedom. The second ratio is the between groups sum of squares divided by the sum of squares for error.

From Table 2, a significant effect of the between subjects factor Urgency(2) can be observed for speed v , acceleration a , spacing s as well as positive relative speed Δv_{pos} and negative relative speed Δv_{neg} . This means that a significant difference, irrespective of time course, was present for speed v , acceleration a , spacing s as well as positive relative speed Δv_{pos} and negative relative speed Δv_{neg} .

Furthermore, the results show that overall time course, represented by the factor Time(3) has a significant effect on speed v , spacing s , positive relative speed Δv_{pos} and negative relative speed Δv_{neg} . This means that the three conditions, irrespective of the factor Urgency(2) had a significant effect on these elements of longitudinal driving behavior. Also the influence of Urgency(2) on time course was significant for speed v , spacing s , positive relative speed Δv_{pos} and negative relative speed Δv_{neg} . This means that time course in the experimental group is significantly different from time course in the control group.

For acceleration a only the factor Urgency(2) has a significant effect. This means that overall acceleration

Table 3. Parameter values of the Intelligent Driver Model (Treiber et al., 2000) for the control group (no emergency situation) and the experimental group (emergency situation).

Parameter	Mean	Std	Min	Max
<i>Control group</i>				
Maximum acceleration a (m/s^2)	0.94	0.68	0.35	2.03
Maximum deceleration b (m/s^2)	0.87	0.34	0.57	1.18
Free speed v_0 (m/s)	29.97	4.02	25.87	34.01
Desired time headway T (s)	0.78	1.06	0.07	2.99
<i>Experimental group</i>				
Maximum acceleration a (m/s^2)	1.46	0.65	0.80	2.14
Maximum deceleration b (m/s^2)	0.97	0.21	0.70	1.18
Free speed v_0 (m/s)	35.27	3.07	32.38	39.51
Desired time headway T (s)	0.25	0.68	0.09	0.45

a different significantly between the two groups. However, overall time course nor Urgency(2) on time course has a significant effect. The effects on deceleration b were not significant.

It can therefore be concluded that emergency situations can be assumed to lead to substantial and significant adaptation effects in longitudinal driving behavior. These effects are characterized by a substantial and significant increase in speed v and acceleration a , together with a significant reduction in spacing s and relative speed Δv .

4.2. Parameter value changes of the Intelligent Driver Model

In the previous subsection we showed that emergency situations lead to substantial and significant adaptation effects in empirical longitudinal driving behavior. In the previous sections we stated that conscious compensation effects in longitudinal driving behavior following an emergency situation may be reflected in parameter values of the Intelligent Driver Model (Treiber et al., 2000). The second research question was therefore: "To what extent are compensation effects in longitudinal driving behavior following an emergency situation reflected in changes in maximum acceleration a_{max} , maximum deceleration b_{max} , free speed v_0 and desired time headway T in the Intelligent Driver Model (Treiber et al., 2000)?"

In order to determine the influence of emergency situations on parameter values of the Intelligent Driver Model we compare parameter values of the control group (no emergency situation) to the parameter values of the experimental group (emergency situation) for this model. We estimated the parameter values of maximum acceleration a , maximum deceleration b , free speed v_0 and desired time headway T separately per driver and per longitudinal position and next calculated the mean values, minimum and maximum values as well as the standard deviations.

In Table 3 the mean values, standard deviations and ranges for the parameter values of the Intelligent Driver Model in case of an emergency situation are presented. This table shows the descriptive statistics of the parameter values for the control group (no emergency situation) as well as for the experimental group (emergency situation).

We start with discussing the effect emergency situations have on maximum acceleration a . Maximum acceleration a in the Intelligent Driver Model (Treiber et al., 2000) represents the maximum acceleration a driver is willing to apply. As an illustration, Figure 5 shows the estimation results for the parameter maximum acceleration a obtained by fitting the Intelligent Driver Model to the observations of the driving simulator for the control group (no emergency situation) and the experimental group (emergency situation).

In the figure the bold blue line represents the estimates of the parameter values, while the thin blue lines represent the variation (expected value plus or minus the standard deviation). The dotted lines represent the start and end of the two stop-and-go waves. From the figure it can be observed that for both groups the parameter value of maximum acceleration a fluctuates considerably over time.

In both groups the two stop-and-go waves do not seem to have a substantial influence on the mean parameter value of maximum acceleration a . Furthermore, it can be observed that the variability between

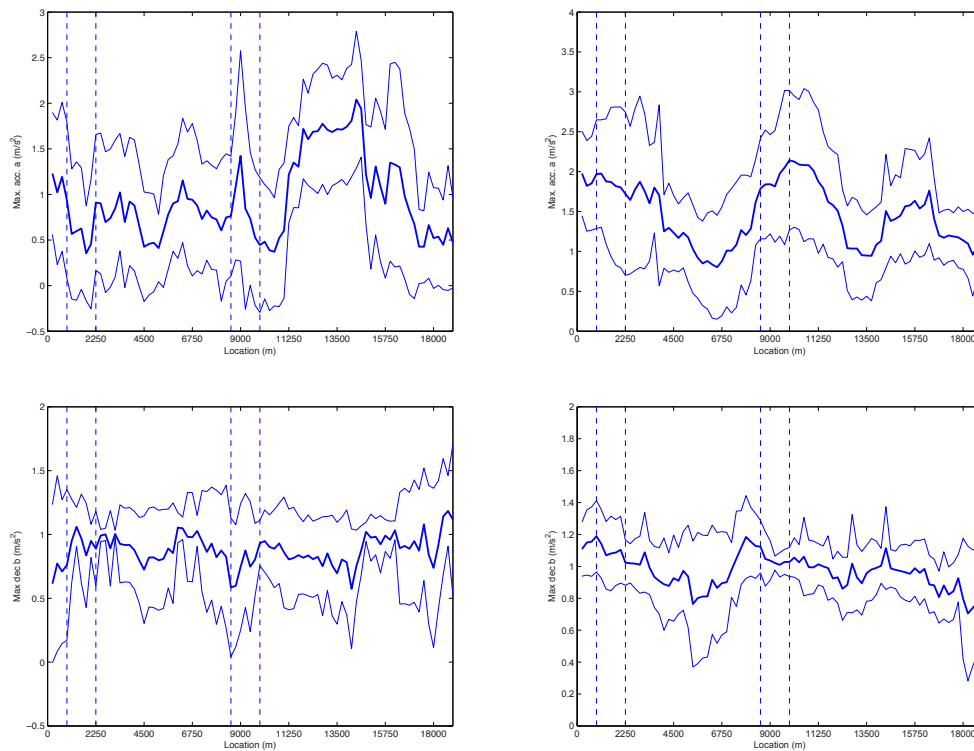


Fig. 5. Parameter estimates of maximum acceleration a (top) and maximum deceleration b (bottom) of the Intelligent Driver Model (Treiber et al., 2000) for the control group (left) and the experimental group (right) in case of an emergency situation. The bold blue line represents the estimates of the parameter values while the thin lines indicate the expected value plus or minus the standard deviation. The four dotted lines represent the start and end of the stop-and-go waves.

drivers is quite substantial, as indicated by the substantial standard deviations.

When comparing the two groups it can be observed from Table 3 as well as from Figure 5 that overall maximum acceleration a is larger in the experimental group than in the control group. The overall mean value of maximum acceleration a in the control group amounted to 0.94 m/s^2 , while in the experimental group the overall mean value amounted to 1.46 m/s^2 . When comparing the value of maximum acceleration a in the control group to values normally used in simulations (Kesting et al., 2010), it can be concluded that this value is quite similar. Overall the variation between drivers was smaller in the experimental group compared to the control group.

From an independent samples t-test it followed that the difference in maximum acceleration a between the control group and the experimental group is significant ($p < .05$). It can therefore be concluded that maximum acceleration a under emergency situations is significantly larger than under normal driving conditions.

In Table 3 also descriptive statistics for maximum deceleration b are presented. Maximum deceleration b in the Intelligent Driver Model (Treiber et al., 2000) represents the maximum deceleration a driver is willing to apply. As an illustration, Figure 5 shows the estimation results for the parameters maximum deceleration b obtained by fitting the Intelligent Driver Model to the observations of the driving simulator for the control group (no emergency situation) and the experimental group (emergency situation). In the figure the bold blue line represents the estimates of the parameter values, while the thin blue lines represent the variation (expected value plus or minus the standard deviation). The dotted lines represent the start and end of the two stop-and-go waves.

From the figure it can be observed that for both groups the parameter value of maximum deceleration b

fluctuates considerably over time. This is a strong indication for a substantial degree of variability within drivers. As was the case with maximum acceleration a , maximum deceleration b also shows substantial differences between drivers as indicated by the substantial standard deviations. In both groups the two stop-and-go waves do not seem to have a substantial influence on the mean parameter value of maximum deceleration b .

When comparing the two groups, it can be observed from Table 3 as well as from Figure 5 that overall maximum deceleration b is larger in the experimental group than in the control group. The overall mean value of maximum deceleration b in the control group amounted to 0.87 m/s^2 , while in the experimental group the overall mean value amounted to 0.97 m/s^2 . When comparing the value of maximum deceleration b in the control group to values normally used in simulations (Kesting *et al.*, 2010), it can be concluded that this value is somewhat lower. Overall the variability between drivers was smaller in the experimental group compared to the control group.

From an independent samples t-test it followed that the difference in maximum deceleration b between the control group and the experimental group is significant ($p < .05$). It can therefore be concluded that maximum deceleration b under emergency situations is significantly larger than under normal driving conditions.

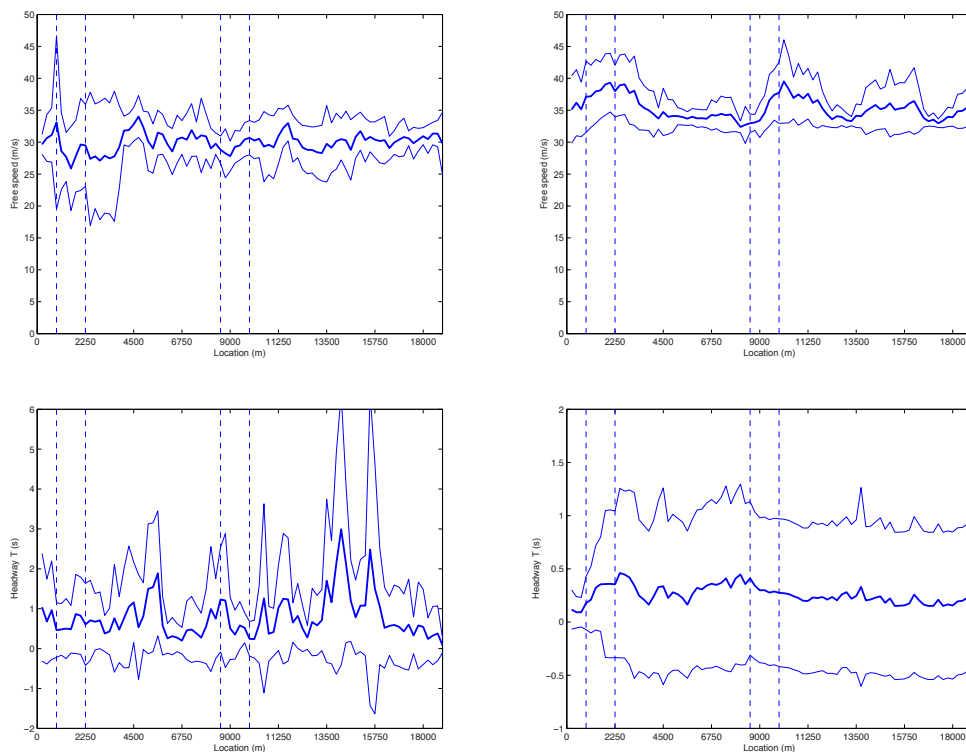


Fig. 6. Parameter estimates of free speed v_0 (top) and desired time headway T (bottom) of the Intelligent Driver Model (Treiber *et al.*, 2000) for the control group (left) and the experimental group (right) in case of an emergency situation. The bold blue line represents the estimates of the parameter values while the thin lines indicate the expected value plus or minus the standard deviation. The four dotted lines represent the start and end of the stop-and-go waves.

In Table 3 also descriptive statistics for free speed v_0 are presented. Again as an illustration, Figure 6 shows the estimation results for the parameter free speed v_0 obtained by fitting the Intelligent Driver Model (Treiber *et al.*, 2000) to the observations of the driving simulator for the control group (no emergency situation) and the experimental group (emergency situation). In the figure the bold blue line represents the estimates of the parameter values, while the thin blue lines represent the variation (expected value plus or

minus the standard deviation). The dotted lines represent the start and end of the two stop-and-go waves.

It can be observed that for both groups the parameter value of free speed v_0 remains fairly constant over time. Furthermore, it can be observed from Figure 6 that the standard deviation is relatively small, which is an indication of a small degree of variability between drivers with regard to this parameter of the Intelligent Driver Model. In both groups the two stop-and-go waves do not seem to have a substantial influence on the mean parameter value of free speed v_0 .

When comparing the two groups it can be observed from Table 3 as well as from Figure 6 that overall free speed v_0 is larger in the experimental group than in the control group. The overall mean value of free speed v_0 in the control group amounted to 29.97 m/s, while in the experimental group the overall mean value amounted to 35.27 m/s. Again, overall the variability between drivers was smaller in the experimental group compared to the control group.

From an independent samples t-test it followed that the difference in free speed v_0 between the control group and the experimental group is significant ($p < .05$). It can therefore be concluded that free speed v_0 under emergency situations is significantly higher than under normal driving conditions.

Finally, in Table 3 also descriptive statistics for desired time headway T are presented. Desired time headway T in the Intelligent Driver Model (Treiber *et al.*, 2000) represents the dynamic component of desired distance to the lead vehicle. This parameter determines the extent to which desired distance to the lead vehicle is dependent on the speed of the following vehicle. Again as an illustration, Figure 6 also shows the estimation results for the parameter desired time headway T obtained by fitting the Intelligent Driver Model to the observations of the driving simulator for the control group (no emergency situation) as well as the experimental group (emergency situation). In the figure the bold blue line represents the estimates of the parameter values, while the thin blue lines represent the variation (expected value plus or minus the standard deviation). The dotted lines represent the start and end of the two stop-and-go waves.

From the figure it can be observed that especially in the control group the parameter value of desired time headway T fluctuates considerably over time. This is a strong indication of a substantial degree of variability within drivers with regard to desired time headway in case of normal driving conditions. In the experimental group the fluctuations over time were considerably smaller. Furthermore, it can be observed from Figure 2 that the variability between drivers is relatively large in both groups. In both groups the two stop-and-go waves do not seem to have a substantial influence on the mean parameter value of desired time headway T .

When comparing the two groups it can be observed from Table 3 as well as from Figure 6 that overall desired time headway T is substantially smaller in the experimental group than in the control group. The overall mean value of desired time headway T in the control group amounted to 0.78s, while in the experimental group the overall mean value amounted to 0.25s. Again, overall the variation between drivers was smaller in the experimental group compared to the control group. From an independent samples t-test it followed that the difference in desired time headway T between the control group and the experimental group is significant ($p < .05$). It can therefore be concluded that desired time headway T under emergency situations is significantly smaller than under normal driving conditions.

From these results it can therefore be concluded that emergency situations lead to substantial and significant changes in parameter values of the Intelligent Driver Model (Treiber *et al.*, 2000). These changes can be regarded as conscious compensation effects as proposed in the theoretical framework. For example, the substantial reduction in desired time headway T in the model can be seen as a compensation effect in order to increase task demands and therefore balance task demands and driver capabilities. The results reported in this subsection can therefore be regarded as an empirical underpinning of the proposed theoretical framework.

4.3. Model performance of the Intelligent Driver Model

In the theoretical framework we however also assumed that when the compensation effects are insufficient in order to restore the imbalance between task demands and driver capabilities, performance effects in longitudinal driving behavior may be the results. These effects may be reflected in the adequacy of car-following. When car-following becomes to a lesser extent a determinant of longitudinal driving behavior, a reduction in model performance of continuous car-following models may be the result.

In order to gain insight into the performance of the Intelligent Driver Model (Treiber *et al.*, 2000) the estimated model was compared to a null model (i.e., the model assuming zero acceleration). In other words: in the null model the parameter values were set to zero, allowing for a good comparison in model performance of the estimated model. From Figure 7 it can be observed for the Intelligent Driver Model that in the control group as well as in the experimental group the estimated models (blue line) outperform the null model.

When comparing the log-likelihoods of the Intelligent Driver Model of the control group to the experimental group it can be observed that performance of the estimated model is quite similar. However, overall performance of the Intelligent Driver Model is somewhat lower in the experimental group compared to the control group. From an independent samples t-test it followed that this difference is significant ($p < .05$).

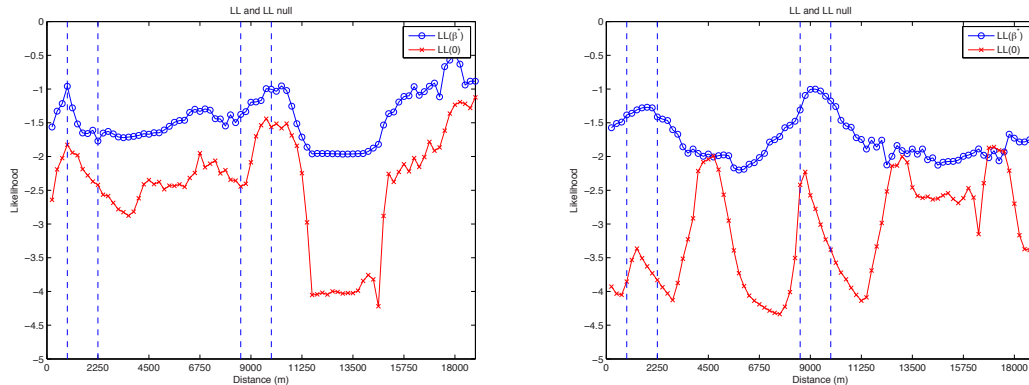


Fig. 7. Performance of the model for the control group (left) and the experimental group (right) compared to the null model (zero acceleration) for the Intelligent Driver Model (Treiber *et al.*, 2000) in case of an emergency situation. The blue line represents the log-likelihoods of the estimated model, while the red line represents the log-likelihoods of the null model. The dotted lines represent the location where the stop-and-go waves started and ended

This reduction in model performance may be assumed to be the result of performance effects in longitudinal driving behavior due to an imbalance between task demands and driver capabilities. Car-following seems to become to a lesser extent a determinant of longitudinal driving behavior. It can however also be due to the characteristics of the IDM (Treiber *et al.*, 2000).

4.4. Perceptual thresholds in psycho-spacing models

In the aforementioned we assumed that compensation effects in longitudinal driving behavior following an imbalance between task demands and driver capabilities may be reflected in the position of the perceptual thresholds used in psycho-spacing models (Leutzbach & Wiedemann, 1986). These perceptual thresholds determine at which relative speeds Δv and spacing s drivers react with a change in their acceleration a . It is however unclear to what extent emergency situations lead to changes in the position of these perceptual thresholds represented by changes in the position of action points in the relative speed - spacing ($\Delta v, s$) plane. The fourth research question was therefore: "To what extent are compensation effects following emergency situations reflected in the position of action points the relative speed - spacing ($\Delta v, s$) plane in a psycho-spacing model?"

In Figure 8 the results are presented of the estimation of the position of action points for the control group (no emergency situation) as well as the experimental group (emergency situation). Overall the figure shows that an overlap in acceleration reductions and accelerations is present. Though this might seem contradictory, this can be explained by the fact that, although a closing relative speed is present, drivers increase their acceleration. This may be caused by the fact that relative speed is not the only determinant of acceleration changes. However, a strong bias can be observed with regard to these overlapping regions when comparing the distributions for acceleration increases and acceleration reductions.

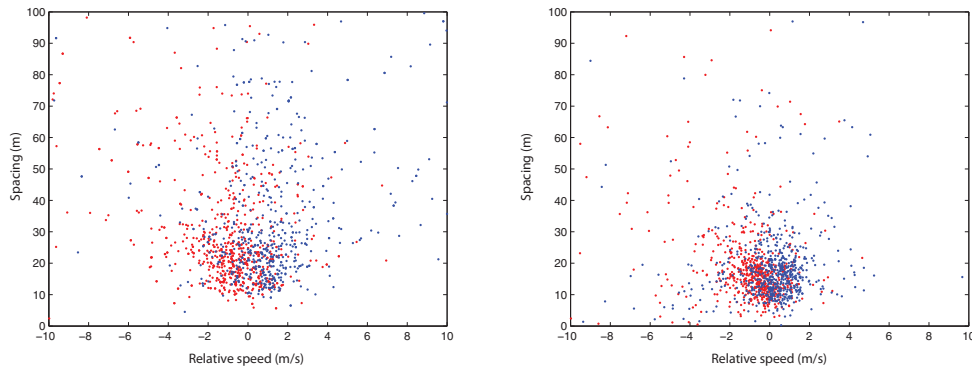


Fig. 8. Distributions of action points for acceleration increases (blue) and acceleration reductions (red) in case of emergency situations. The left graph represents the control group (no emergency situation) while the right graph shows the action points for the experimental group (emergency situation).

When comparing the distributions of action points of the control group (no emergency situation) and the experimental group (emergency situation) in Figure 8, it can be observed that in case of this adverse condition action points are much more concentrated at especially smaller values of spacing s than in the control group.

Secondly, it becomes clear from Figure 8 that, in contrast with the control group, in the experimental group drivers react to considerably small values of relative speed Δv . This may be due to the fact that drivers generally keep smaller values of spacing s in case of emergency situations. From the Kolmogorov-Smirnov test it followed that the difference between the two distributions is significant ($p < .05$).

In order to further quantify the influence emergency situations have on the position of action points in the psycho-spacing model, we aimed at finding the coefficients of the polynomials in the second degree that fitted the action points displayed in Figure 8 in a least squares sense. Here we fitted polynomials for acceleration increases and reductions for the control group as well as for the experimental group. The results are shown in Figure 9 and Table 4. In the table the coefficients p_n are displayed as well as the Mean Square Error (MSE) and the Mean Absolute Error (MAE).

Table 4. Results curve fitting for acceleration reductions and increases for the reference datasets and the datasets with the adverse conditions.

	p_1	p_2	p_3	MSE	MAE
Acc red ref	.0002	-.0464	.5247	5.04	10.64
Acc inc ref	-.0005	.0739	-.7439	5.76	10.76
Acc red evac	.0007	-.1053	1.5367	15.66	20.20
Acc inc evac	.0000	.0013	1.5141	12.32	17.66

From the figure as well as from the table it can be observed that the shape of the perceptual thresholds in the control group differ substantially from the shape of the perceptual thresholds in the experimental group. These graphs show that the perceptual thresholds for acceleration increases and reductions are much closer together in the group with the emergency situation than is the case in the control group. Furthermore it can be observed from these graphs that the perceptual thresholds for acceleration increases and acceleration reductions are asymmetric. This is especially the case in the dataset with the adverse condition.

From the aforementioned it can therefore be concluded that emergency situations have a substantial influence on perceptual thresholds represented by the position of action points in the relative speed - spacing ($\Delta v, s$) plane in psycho-spacing models. In the context of the theoretical framework it can be concluded that these changes in the position of the perceptual thresholds are a strong indication for the presence of compensation effects and may serve as an empirical underpinning of the framework.

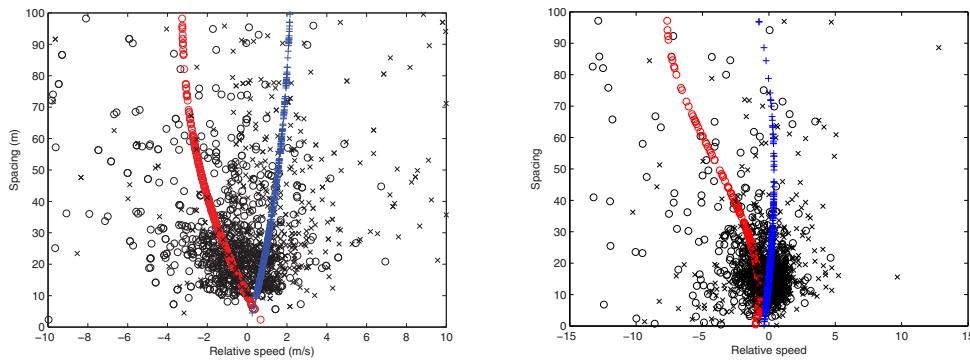


Fig. 9. Distributions of action points for acceleration increases (blue) and acceleration reductions (red) in case of emergency situations. The left graph represents the control group (no emergency situation) while the right graph shows the action points for the experimental group (emergency situation).

4.5. Sensitivity towards relative speed and spacing at action points

Finally it was assumed in the proposed theoretical framework that performance effects resulting from an imbalance between task demands and driver capabilities may be reflected in the sensitivity of acceleration a at the action points in a psycho-spacing model (Leutzbach & Wiedemann, 1986) towards lead vehicle related stimuli (relative speed Δv and spacing s). It is however not yet clear to what extent emergency situations actually influence this sensitivity. The fifth research question was therefore: "To what extent are performance effects following emergency situations reflected in the sensitivity towards relative speed Δv and spacing s at action points in a psycho-spacing model?"

The extent to which emergency situations influence the sensitivity of acceleration a at the action points towards relative speed Δv and spacing s was determined through a Multivariate Regression Analysis (MRA) using the model presented in the Research Method section.

Table 5 shows the results of the MRA for the normal driving condition (control group) and the emergency situation (experimental group). Overall, it can be concluded that, in the group with the emergency situation as well as in the control group, drivers accelerate less strong at larger values of s in response to speed differences with the lead vehicle Δv . As an example, the model is displayed in Figure 10.

Table 5. Results Multivariate Regression Analysis for the experimental group and the control group. The values of b_x refer to the parameter values incorporated in the models, while the error refers to the sum of the residuals. MSE refers to the Mean Squared Error.

	b_1	b_2	Error	MSE
<i>Reference dataset</i>				
Model 1	0.30	-0.01	489.80	0.11
Model 2	1.44	0.07	482.67	0.10
Model 3	0.26	-0.01	706.16	0.23
Model 4	2.86	-0.19	685.51	0.21
<i>Emergency situations</i>				
Model 1	0.13	-0.01	1099.30	0.59
Model 2	0.21	0.10	1071.70	0.56
Model 3	0.30	0.01	1567.60	1.21
Model 4	1.52	-0.03	1523.50	1.14

It can be observed that the value of b_1 is substantially lower in the group with the emergency situation compared to b_1 in the control group. The value of the sensitivity parameter b_2 shows a slight increase.

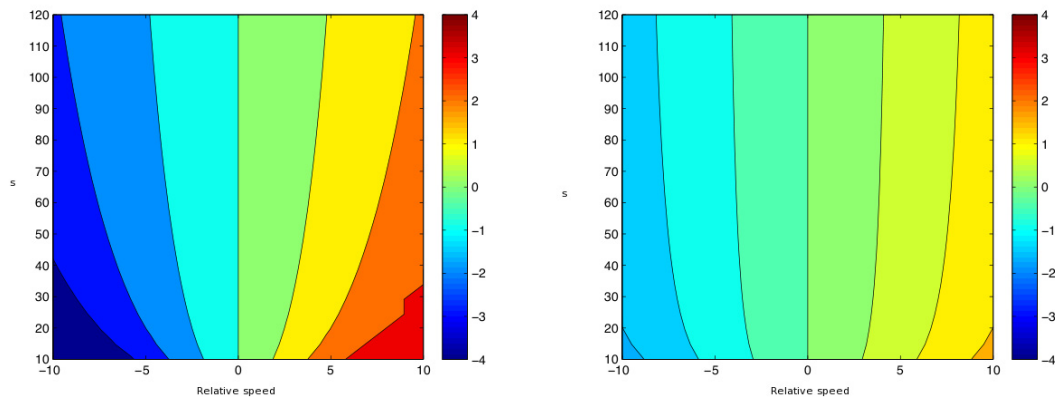


Fig. 10. Distributions of action points for acceleration increases (blue) and acceleration reductions (red) in case of emergency situations. The left graph represents the control group (no emergency situation) while the right graph shows the action points for the experimental group (emergency situation).

The aforementioned means that acceleration a is less sensitive to relative speed Δv in the group with the emergency situation compared to the control group.

Furthermore, it follows from the reported error and MSE in Table 5 that the error and MSE in the group with the emergency situation are substantially larger than in the control group. This means that the models less adequately describe acceleration in the group with the emergency situation than in the control group.

From the aforementioned it can be concluded that performance effects in longitudinal driving behavior are reflected in a reduction in the sensitivity of acceleration a towards relative speed Δv at action points in a psycho-spacing models. Furthermore it can be argued that performance effects are also reflected in the fact that the MSE is substantially higher in the condition with the emergency situation as this is an indication for the fact that presumably car-following becomes to a lesser extent a determinant of the acceleration at the action points.

5. Discussion

Emergency situations have been shown to have a substantial impact on traffic flow operations. However, since emergency situations have a low incidence, little knowledge is available on how to respond to them. In order to examine whether solution approaches, such as lane reversal, are effective simulation studies must be performed.

However, it was not yet clear to what extent longitudinal driving behavior actually changes following an emergency situation as well as how these changes in behavior can be explained theoretically. Therefore in this paper we presented extensive empirical analyses of adaptation effects in longitudinal driving behavior following an emergency situation as well as introduced a new theoretical framework, aimed at explaining these adaptation effects.

In this paper we showed that emergency situations lead to substantial adaptation effects in longitudinal driving behavior. We showed that this adverse condition leads to significant changes in speed, acceleration and spacing (distance to the lead vehicle). These adaptation effects may be assumed to have a substantial influence on traffic flow operations. Recent research has for example shown that these effects lead to an increase in capacity (Hoogendoorn *et al.*, 2013).

To empirically underpin the proposed theoretical framework (analysis of compensation and performance effects), we analyzed parameter value changes and model performance of the IDM (Treiber *et al.*, 2000) as well as determined the changes in the position of the so-called perceptual thresholds in a psycho-spacing model.

We showed that emergency situations lead to substantial changes in parameter values in the IDM (Treiber *et al.*, 2000). In this paper we argued that these changes can be considered as conscious compensation effects as proposed in the framework. Furthermore we determined that emergency situations lead to a reduction in model performance. We argued that this might be a result of performance effects in longitudinal driving behavior. However, the reduction in model performance could also be due to the characteristics of the model itself.

We also showed that emergency situations have a substantial influence on the position of the perceptual thresholds in the relative speed - spacing ($\Delta v, s$) plane. These changes in the perceptual thresholds can be regarded as compensation effects in longitudinal driving behavior as proposed in the theoretical framework.

Furthermore we showed that the sensitivity of acceleration a towards lead vehicle related stimuli (i.e., relative speed Δv and spacing s) at the action points reduces substantially following emergency situations. Driver seem to become less sensitive towards behavior of the lead vehicle, which was argued to reflect the performance effects as proposed in the theoretical framework.

It can therefore be concluded that compensation effects and performance effects in longitudinal driving behavior following an emergency situation may be reflected in parameter value changes and model performance in continuous car-following models as well as in the position of action points as well as the sensitivity of acceleration towards lead vehicle related stimuli at the action points in psycho-spacing models.

The aforementioned can be regarded as a first step towards the empirical underpinning of the proposed theoretical framework. However, in order to further empirically underpin the framework firstly more insight into task demands and driver capability is needed. This means that insight is needed into the actual influence of static (age, driving experience) and dynamic driver characteristics (activation level). It is therefore recommended to perform future research into the effects of driver characteristics on driver capability. Furthermore more insight is needed into the effect emergency situations have on task demands. It is recommended to perform future research as to the extent to which emergency situations actually influence task demands of the longitudinal driving task.

Secondly, in this paper we used the parameter value changes and changes in model performance as well as the changes in the position of the perceptual thresholds and sensitivity towards lead vehicle related stimuli at these action points as an empirical underpinning of the proposed theoretical framework. However, these effects can only be regarded as mere indications of compensation and performance effects. We therefore need to develop adequate measures to determine compensation and performance effects in relation to emergency situations.

Thirdly, we analyzed adaptation effects in longitudinal driving behavior following an emergency situation using driving simulator data. Until now, the driving simulator has not been validated for this purpose, although relative validity may be assumed. We therefore recommend to perform a validation study aimed at determining the absolute and relative validity of the driving simulator in relation to longitudinal driving behavior in case of emergency situations. Finally, a relatively small sample size was used in the experiment. We therefore recommend to replicate the conducted experiment using a larger sample size.

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